Simulative Vehicle Concept Optimisation considering Lap Time as Objective Function

AVL International Simulation Conference 2019 – Day 1 (October 22, 2019)

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https://doi.org/10.24355/dbbs.084-202107071036-0

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https://doi.org/10.24355/dbbs.084-202107071036-0

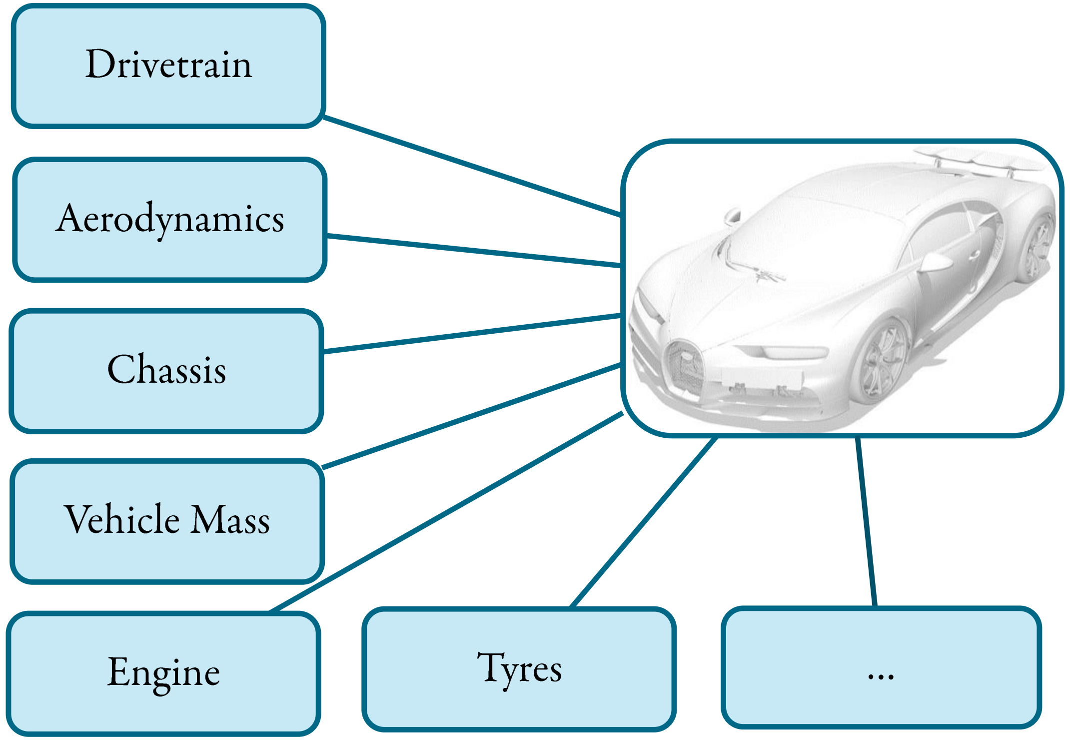
1. MOTIVATION AND OBJECTIVES

Motivation:

- Identification of lap time potentials for a vehicle concept

Objectives:

- Define targets for vehicle parameters
- Time-efficient evaluation with high accuracy
- Compare various tracks and the influence on the optimisation results



Optimisation process considering lap time as objective function

https://doi.org/10.24355/dbbs.084-202107071036-0

2. LAP TIME OPTIMISATION

Optimisation Process – Lap time

Selection of variable vehicle parameters

↓

Determination of the variation range of the vehicle parameters

↓

Dependency modelling

- Technical project specifications as well as sensitivity studies deliver variable vehicle parameters
- Parameter space determined by:
  - Legal requirements
  - Technical feasibility
- Dependency modelling to link parameters that are influencing each other

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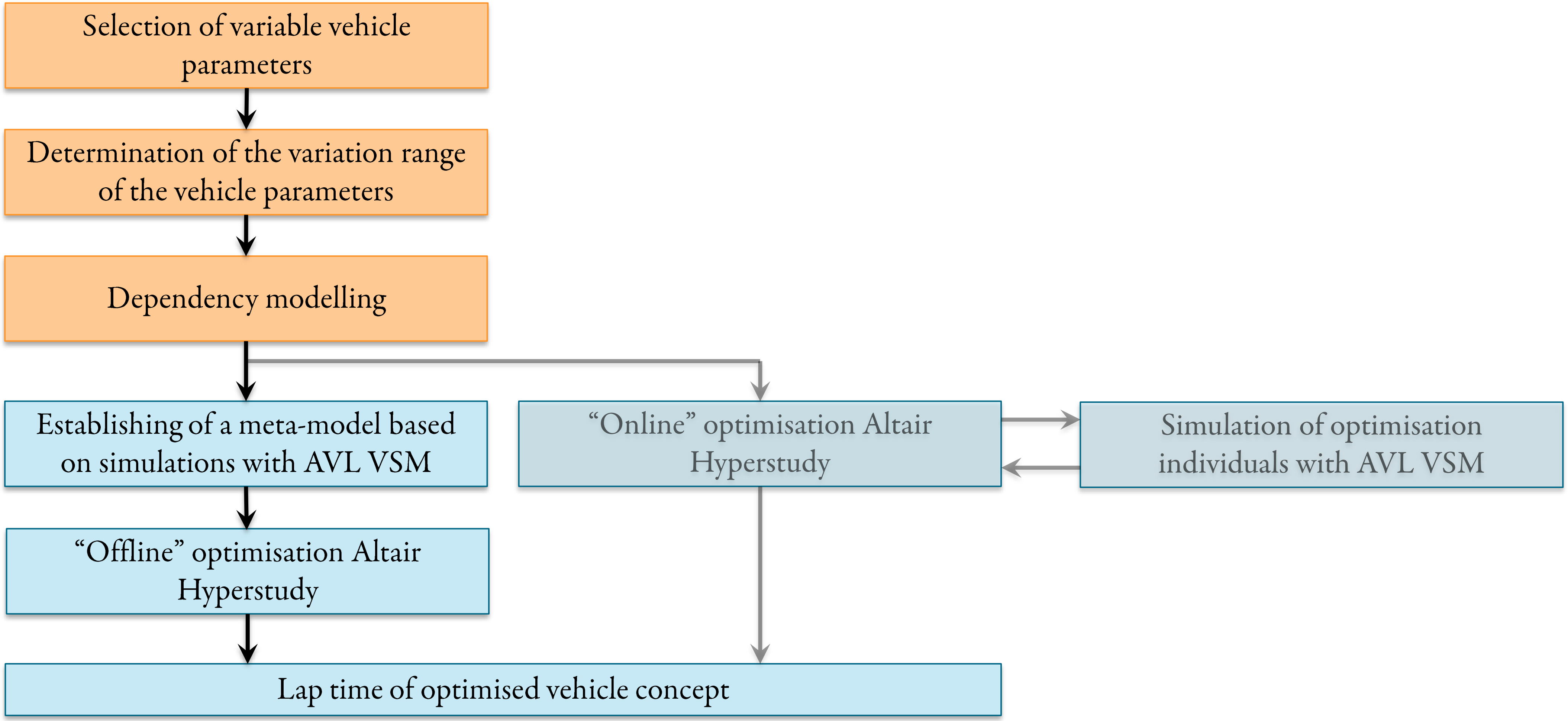
2. LAP TIME OPTIMISATION

Optimisation Process – Lap time



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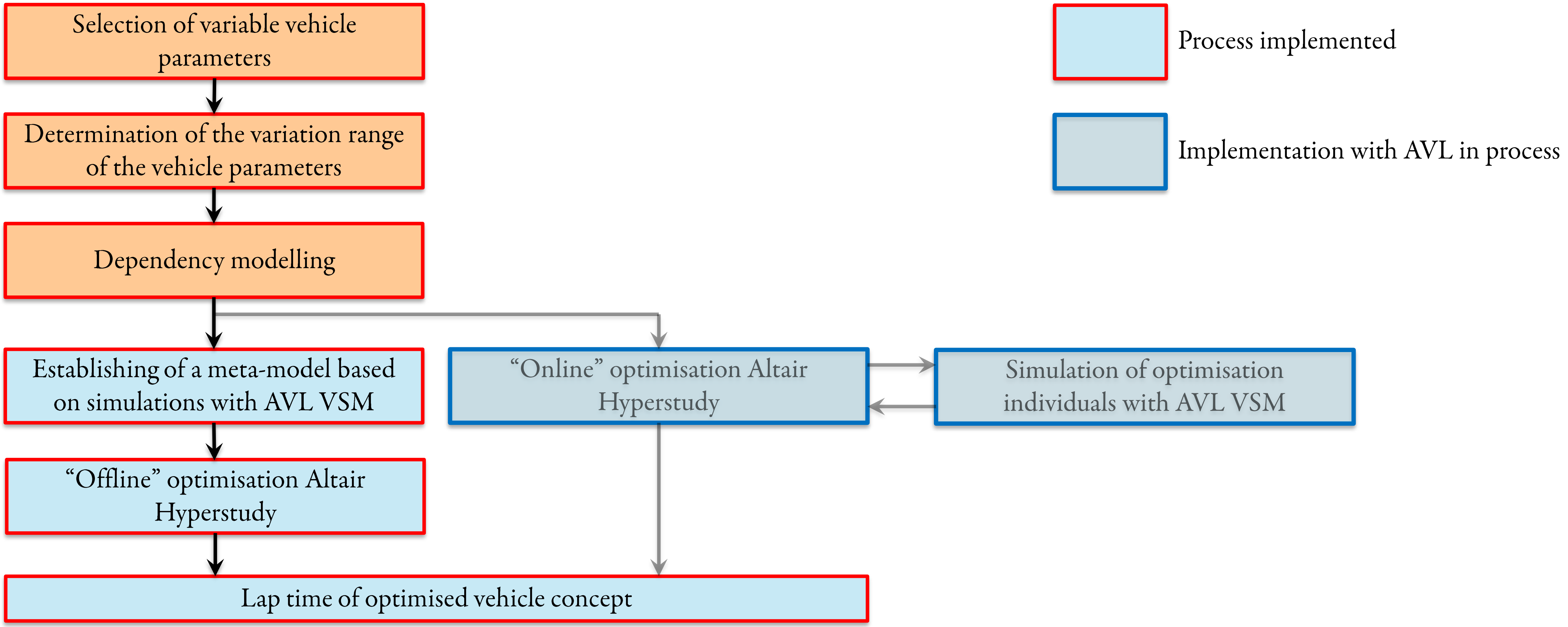

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2. LAP TIME OPTIMISATION

Variable Vehicle Parameters for the Optimisation

1	Mass (with Driver and Fuel)	kg	1,500	2,300
2	Power	kW	883	1,324
3	Grip	%	90	100
4	Centre of Gravity Height	mm	250	450
5	Downforce Coef. – Front Axle	-	0	0.75
6	Downforce Coef. – Rear Axle	-	0	1
7	Axle Load Distribution	%	30	52
8	Track Width – Front Axle	mm	1,600	1,900
9	Track Width – Rear Axle	mm	1,600	1,900
10	Anti-roll Bar Stiffness – Front Axle	N/mm	0	110

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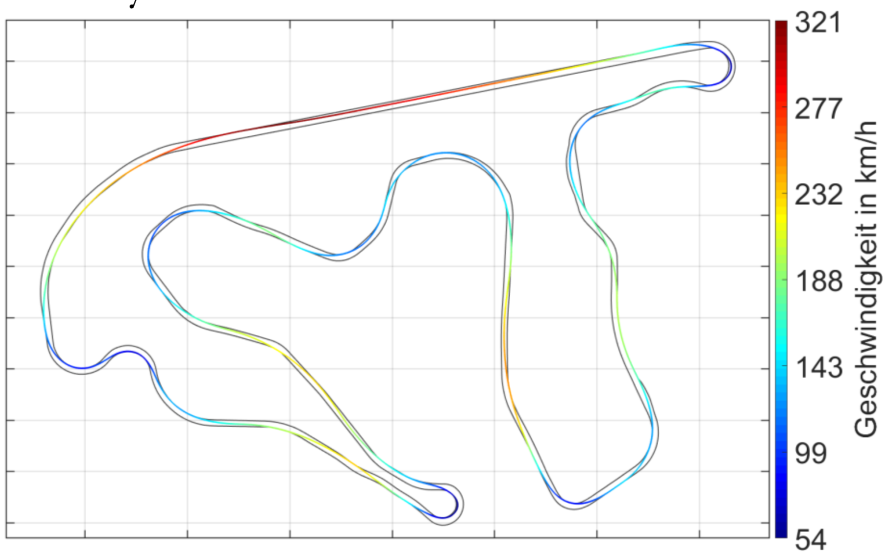
2. LAP TIME OPTIMISATION

Generation of the Meta-model

Assessment Basis:

Workstation: Intel Xeon Gold 6134 CPU with 3.2 GHz
Calculation: Parallel on 8 cores
Track: Nardo Handling (6.139 km)
Track layout:



Calculation time for 100 vehicle configurations:
12.3 minutes

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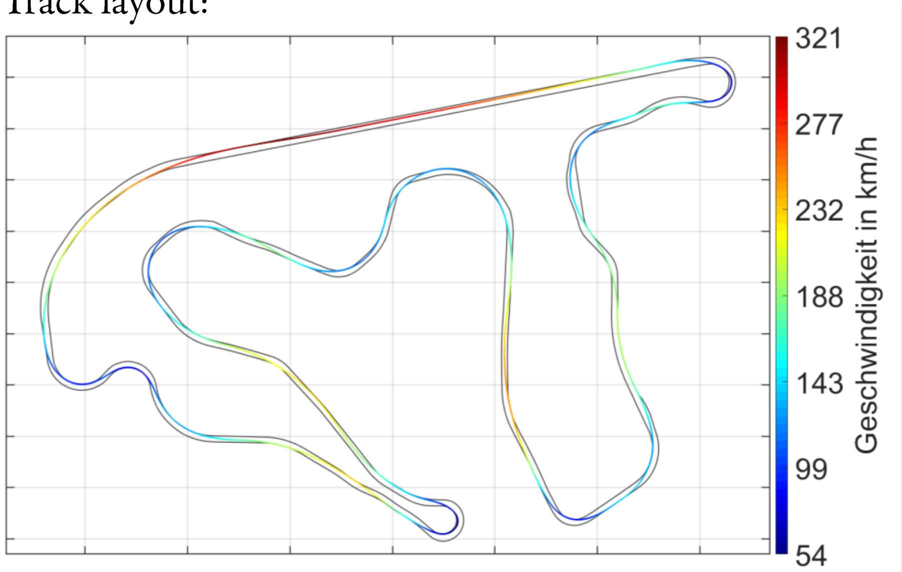

Calculation time for 100 vehicle configurations:
12.3 minutes

Full factorial DoE: $\mathbb{N}(\text{Simulation}) = n_{\text{Support points}}{}^{n_{\text{Parameter}}}$

No. of parameters	No. of support points: 2	3	4	5	6	7	8	9	10
2	$2^2 = 4$	9	16	25	36	49	64	81	100
3	8	27	64	125	216	343	512	729	1000
4	16	81	256	625	1296	2401	4096	6561	10000
5	32	243	1024	3125	7776	16807	32768	59049	100000
6	64	729	4096	15625	46656	117649	262144	531441	1E+06
7	128	2187	16384	78125	279936	823543	2E+06	5E+06	1E+07
8	256	6561	65536	390625	2E+06	6E+06	2E+07	4E+07	1E+08
9	512	19683	262144	2E+06	1E+07	4E+07	1E+08	4E+08	1E+09
10	1024	59049	1E+06	1E+07	6E+07	3E+08	1E+09	3E+09	1E+10
11	2048	177147	4E+06	5E+07	4E+08	2E+09	9E+09	3E+10	1E+11
12	4096	531441	2E+07	2E+08	2E+09	1E+10	7E+10	3E+11	1E+12

- Calculation time < 1 day
- Calculation time < 1 week
- Calculation time < 1 month
- Calculation time > 1 month

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2. LAP TIME OPTIMISATION

Generation of the Meta-model

Relevant areas for fast concept studies not suitable for full factual examination

→ Meta-model to rapidly predict lap times needs to be developed

Full factual DoE: $\mathbb{N}(\text{Simulation}) = n_{\text{Support points}}{}^{n_{\text{Parameter}}}$

No. of parameters	No. of support points								
	2	3	4	5	6	7	8	9	10
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2. LAP TIME OPTIMISATION

Generation of the Meta-model

How many designs do we need for an adequate meta-model?

Relevant areas for fast concept studies not suitable for full factual examination

→ Meta-model to rapidly predict lap times needs to be developed

Full factorial DoE: $\mathbb{N}(\text{Simulation}) = n_{\text{Support points}}^{\;n_{\text{Parameter}}}$

No. of parameters	No. of support points: 2	3	4	5	6	7	8	9	10
2	$2^2 = 4$	9	16	25	36	49	64	81	100
3	8	27	64	125	216	343	512	729	1000
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	32	243	1024	3125	7776	16807	32768	59049	100000
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2. LAP TIME OPTIMISATION

Generation of the Meta-model

Factors that influence prediction accuracy:

- Size of the DoE and algorithm for creating the DoE
- Type, quantity and variation range of the variable vehicle parameters
- Algorithm for creating the meta-model based on the DoE

Full factorial DoE: $\mathbb{N}(\text{Simulation}) = n_{Support\ points}{}^{n_{\text{Parameter}}}$

No. of parameters	No. of support points								
	2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
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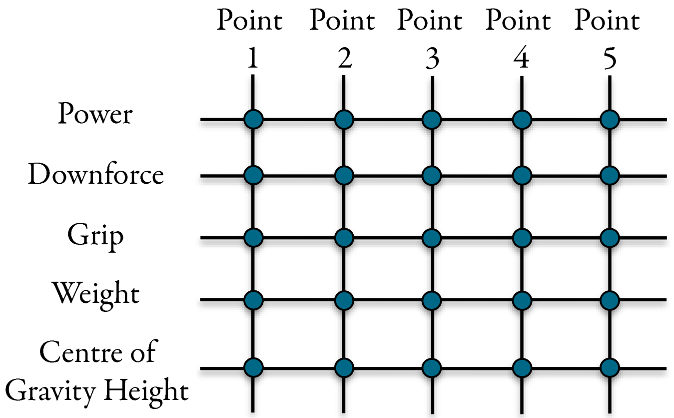
2. LAP TIME OPTIMISATION

Generation of the Meta-model

Full Factorial DoE

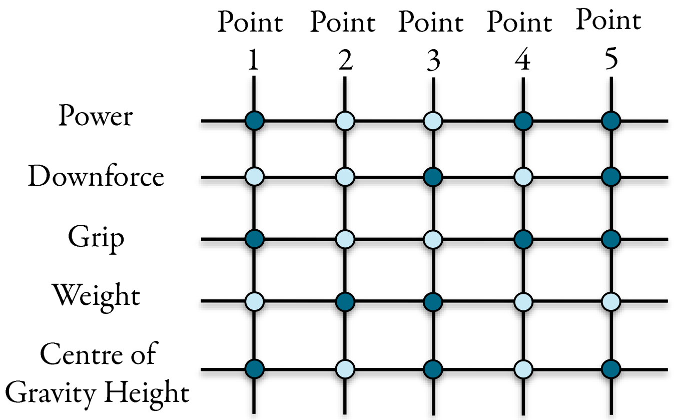


+ Very high accuracy
+ Very good system knowledge

- Very high computational effort
  → Unconvertible for real world problems

Serves as ideal reference in the following example for evaluation of reduced DoE meta-models

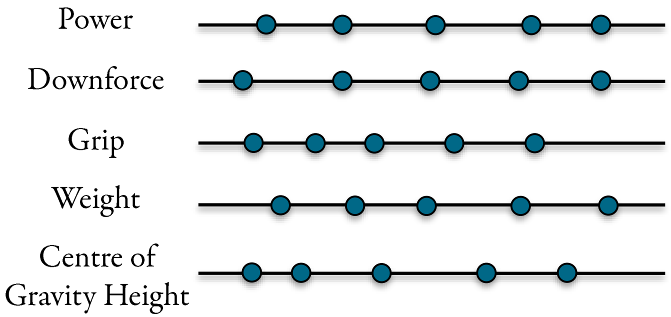
Fractional Factorial DoE



+/- Less computational effort, but still hard to apply to real world problems

- Accuracy depending on amount and choice of design points → Difficult to predict

Modified Extensible Lattice Sequence DoE



+ Best accuracy with least computational effort

Serves as DoE algorithm for the following study

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2. LAP TIME OPTIMISATION

Generation of the Meta-model

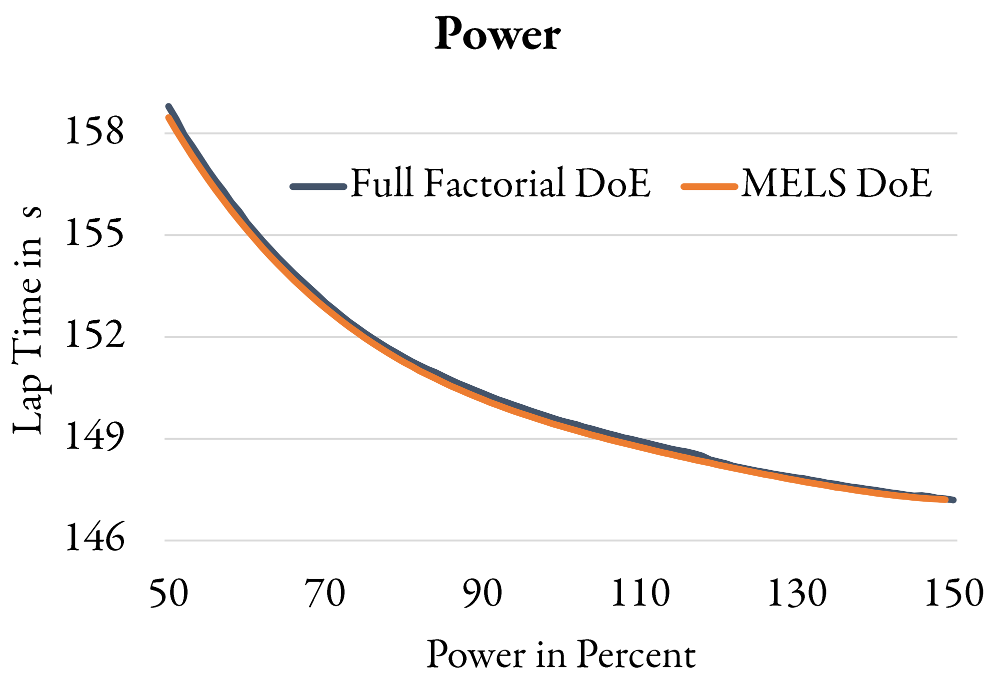
Best Practice to generate the Meta-model:

→ Meta-model works well for $a = [32\,;64]$ multiplied by the number of simulations recommended by the algorithm:

$$\mathbb{N}(\text{Simulation}) = a \cdot \frac{1.1(n_{\text{Parameter}} + 1)(n_{\text{Parameter}} + 2)}{2}$$

→ Quantitative precision: 99 to 99.95 %

→ Is determined to give right design decisions for vehicle concept



Precision of the meta-model	
Vehicle parameters	**Root Mean Square Error**
Power	0.134 s
Total Downforce	0.025 s
Grip	0.119 s
Height of the centre of gravity	0.129 s
Weight	0.078 s

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Basis for later optimisation

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3. DEPENDENCY MODELLING

Aerodynamics

Dependence of Drag and Downforce:

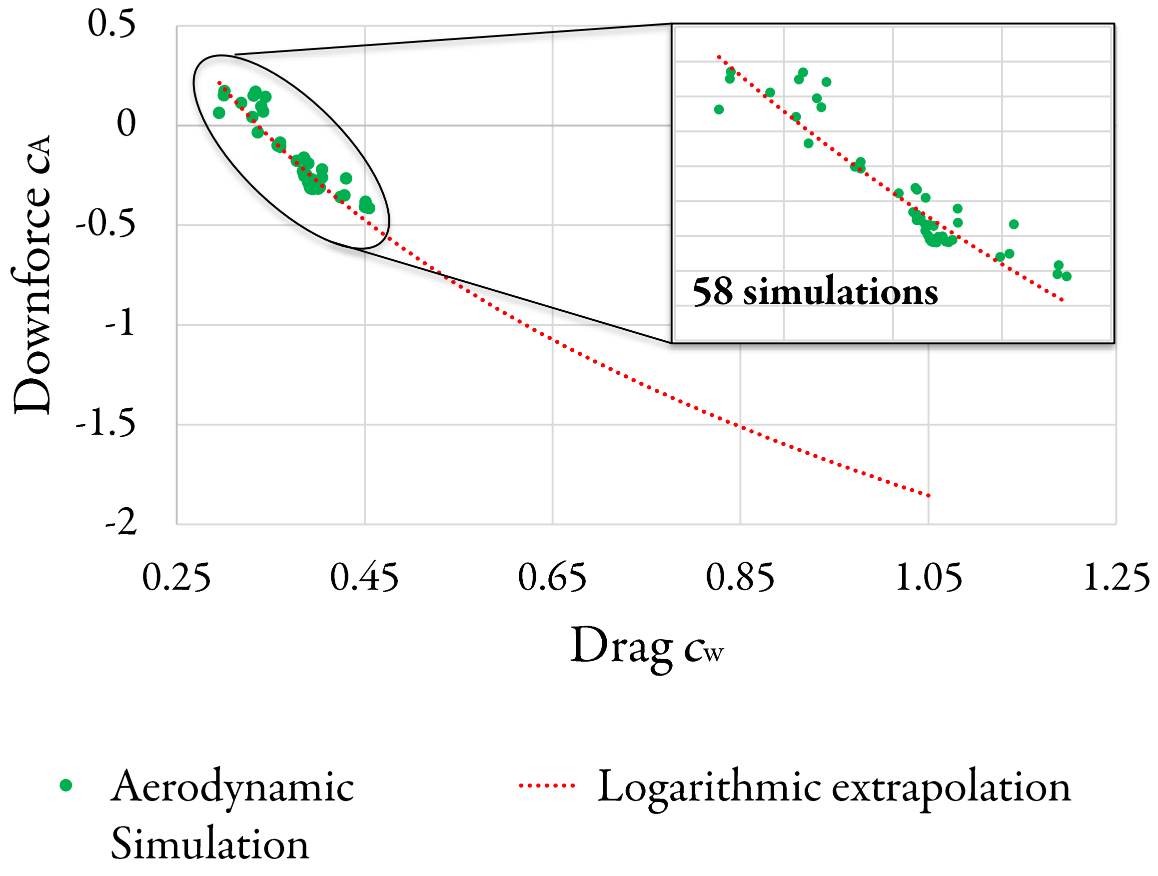
- Dependency model based on aerodynamic simulation data
- 58 simulations as data basis
- Logarithmic extrapolation provides the connection between downforce and drag:

$$c_A = -1{,}63 \cdot \ln(c_W) - 1{,}7757$$

and

$$c_W = e^{\frac{c_A + 1{,}7757}{(-1{,}63)}}$$

- Future goal: Include thermal assessment



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3. DEPENDENCY MODELLING

Power-to-weight ratio

Dependence of Mass and Power:

- Constant power-to-weight ratio for the powertrain:

$$\text{Power—to—weigth ratio}_{\text{Powertrain}} = \text{const} = \frac{m_{\text{Powertrain}}}{P_{\text{Engine}}}$$

- Total vehicle mass is calculated from vehicle and powertrain mass:

$$m_{\text{Total}} = m_{\text{Vehicle}} + m_{\text{Powertrain}}$$

Mass of the vehicle without powertrain:

"Lightweight design"

900 kg | 1,390 kg

Mass of the powertrain:

$$m_{\text{Powertrain}} = \text{Power—to—weight ratio}_{\text{Powertrain}} \cdot P_{\text{Engine}}$$

608 kg | 912 kg

Power:

883 kW | 1,324 kW

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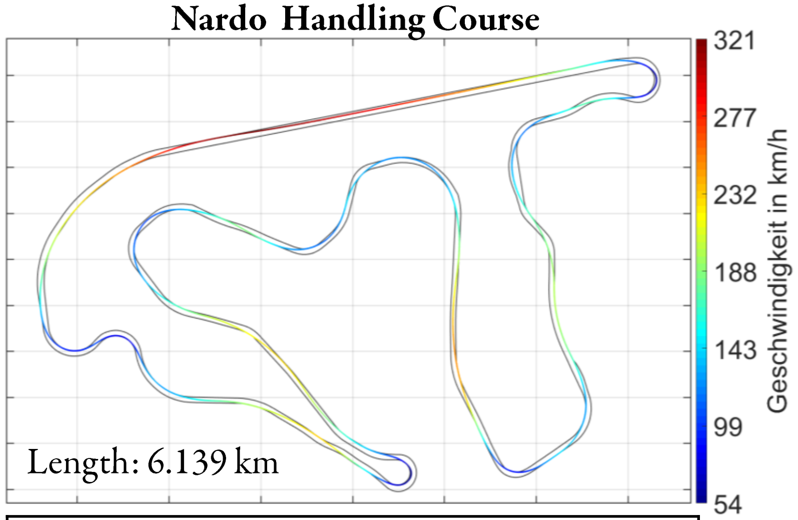
4. STUDY RESULTS

- Generation of the meta-model and optimisation with Altair Hyperstudy based on simulations with AVL VSM
- Assessment basis:
  - **DoE**: Modified Extensible Lattice sequence with 4672 individuals
  - **Meta-model**: Radial Basis Function
  - **Optimisation**: Genetic algorithm

Validation of the optimisation results shows that the meta-model has a high level of precision:
Average of 0.13 % deviation from the simulation



Lap Time in s			
Optimisation-result	Simulation	Δ in s	Δ in %
149.24	149.32	0.07	0.05
135.07	134.80	0.27	0.20
134.44	134.24	0.20	0.15
134.05	133.91	0.13	0.10
133.81	133.77	0.04	0.03
133.63	133.39	0.24	0.18
...	...	...	...
133.38	133.21	0.17	0.13
133.21	132.92	0.29	0.22
132.84	132.73	0.11	0.08
	Mean value	**0.17**	**0.13**
	Maximum deviation	**0.29**	**0.22**

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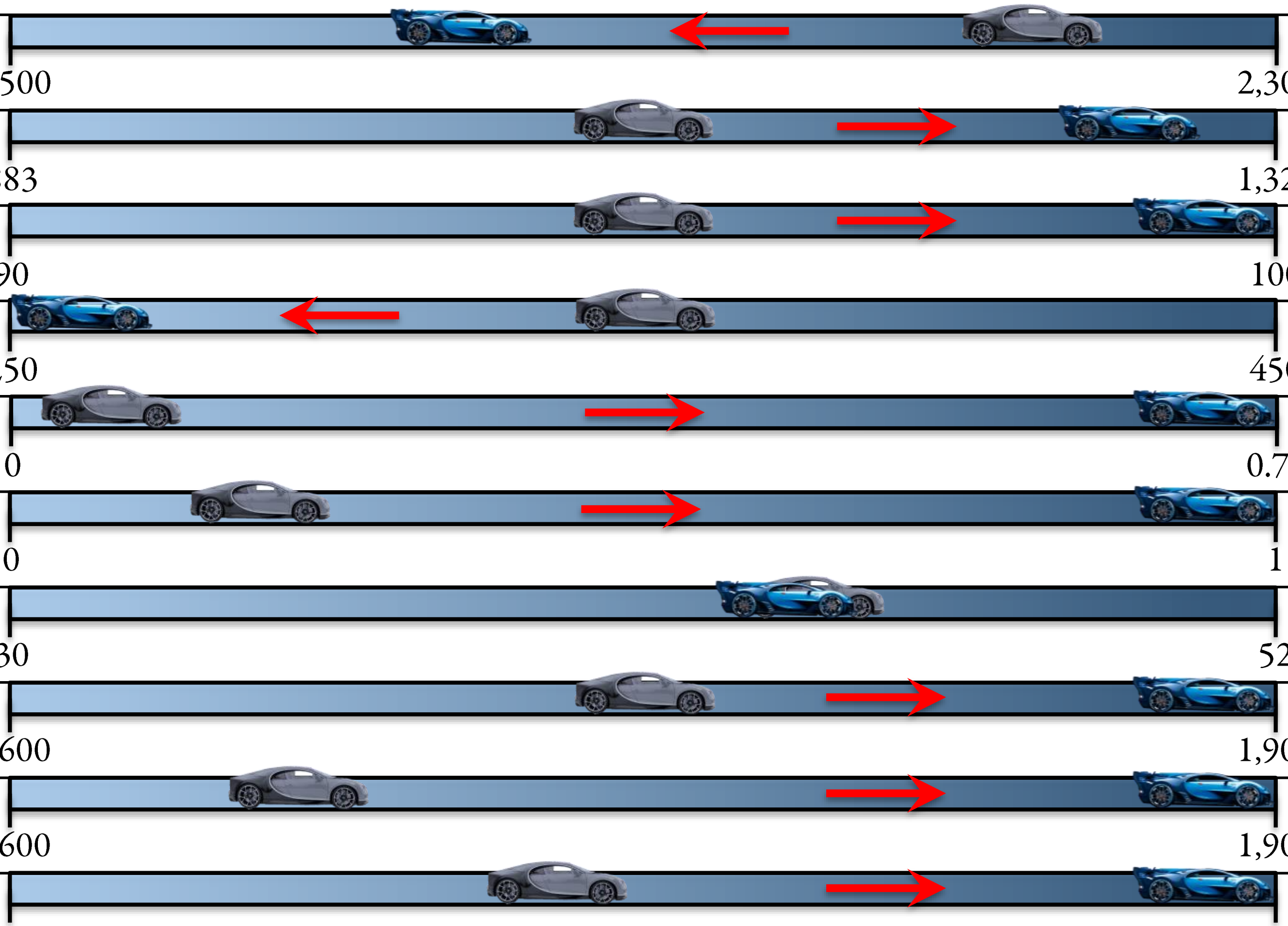

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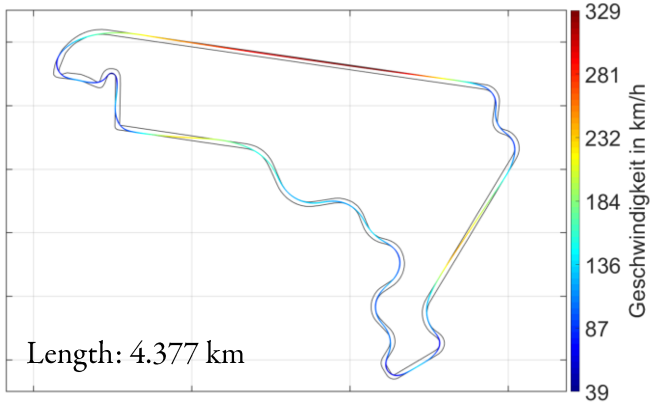
4. STUDY RESULTS

- Low
- Middle
- High

Autodrómo Hermanos Rodríguez "Curvy Handling Scenario"	Nardo Handling Course "Intermediate Scenario"	Autodromo Nazionale Monza "High-Speed Scenario"

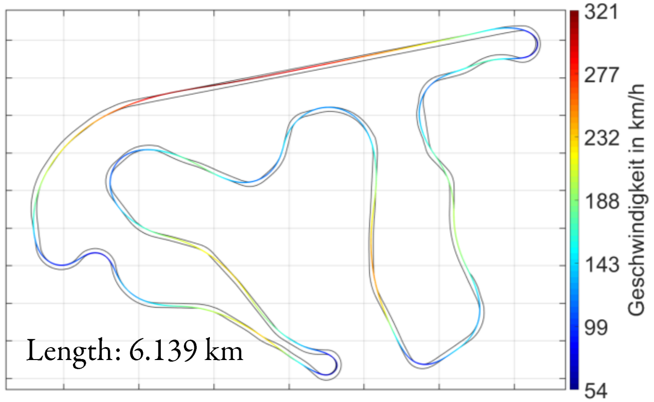
Autodrómo Hermanos Rodríguez

"Curvy Handling Scenario"



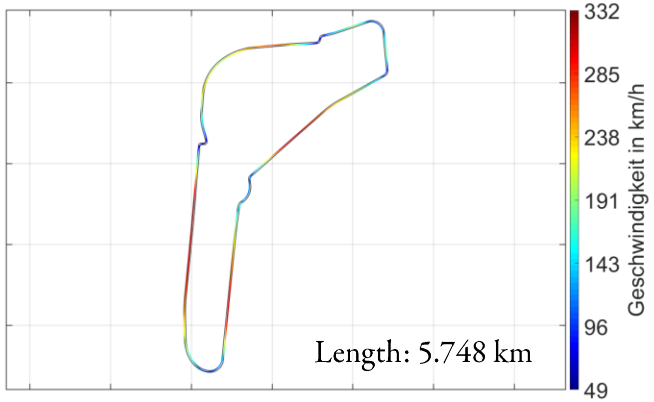
Nardo Handling Course

"Intermediate Scenario"



Autodromo Nazionale Monza

"High-Speed Scenario"



	Autodrómo Hermanos Rodríguez	Nardo Handling Course	Autodromo Nazionale Monza
Average speed v_{avg} in $\frac{km}{h}$	135.4	151.1	179.0
Average power output P_{avg} in kW	402.5	451.2	614.7
Average curvature of the ideal line κ_{avg} in $\frac{1}{m}$	0.0092	0.0073	0.0048

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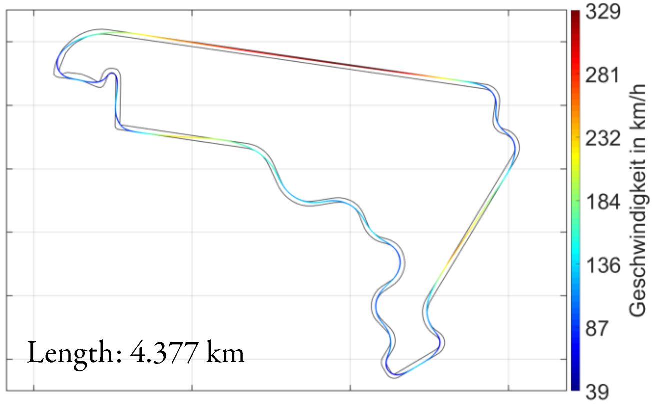
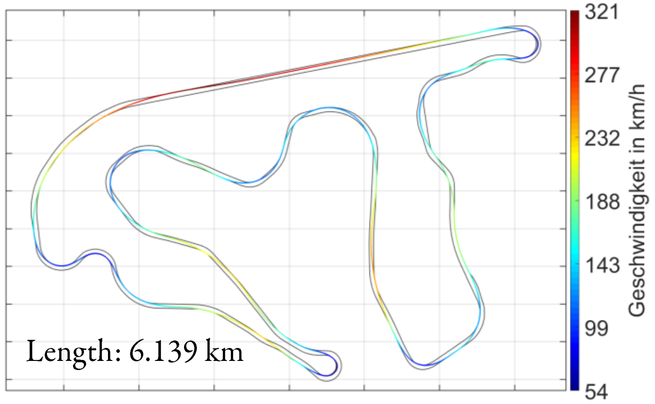
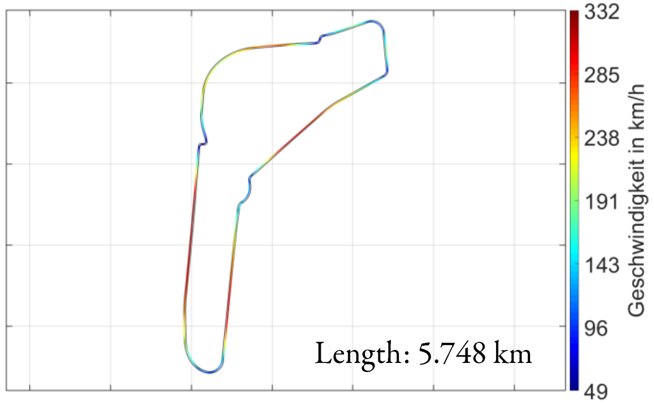
4. STUDY RESULTS

	Autodrómo Hermanos Rodríguez “Curvy Handling Scenario”	Nardo Handling Course “Intermediate Scenario”	Autodromo Nazionale Monza “High-Speed Scenario”
			
Mass of the powertrain in kg	608 – 912	608 – 912	608 – 912
Power in kW	883 – 1,324	883 – 1,324	883 – 1,324
Total Downforce	0 – 1.75	0 – 1.75	0 – 1.75

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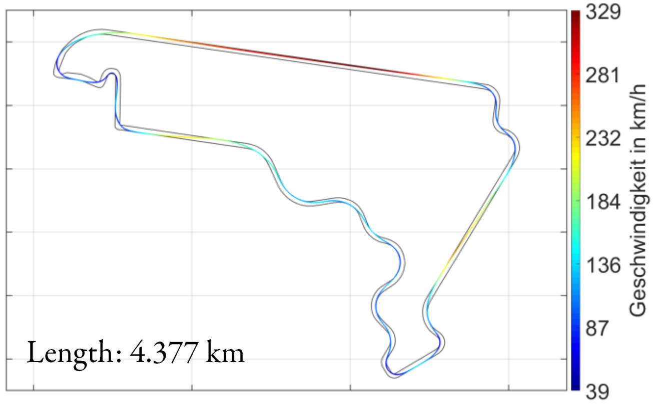
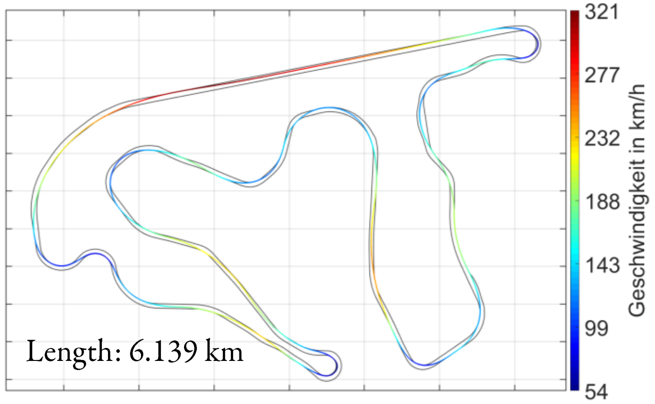
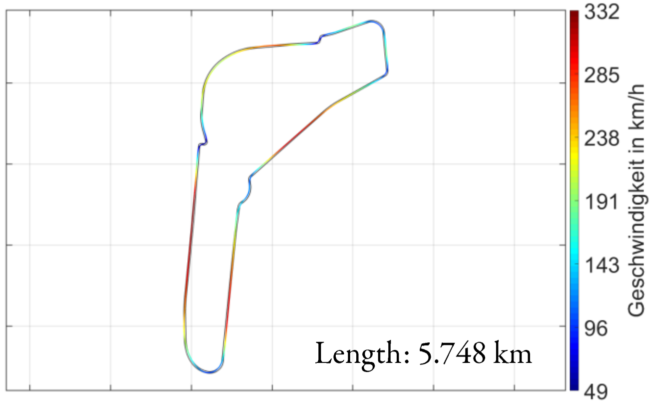
4. STUDY RESULTS

Autodrómo Hermanos Rodríguez	Nardo Handling Course	Autodromo Nazionale Monza
"Curvy Handling Scenario"	"Intermediate Scenario"	"High-Speed Scenario"







→ Maximum Downforce → Less Power for lower Mass	⟷	→ Maximum Power → Less Downforce for lower drag

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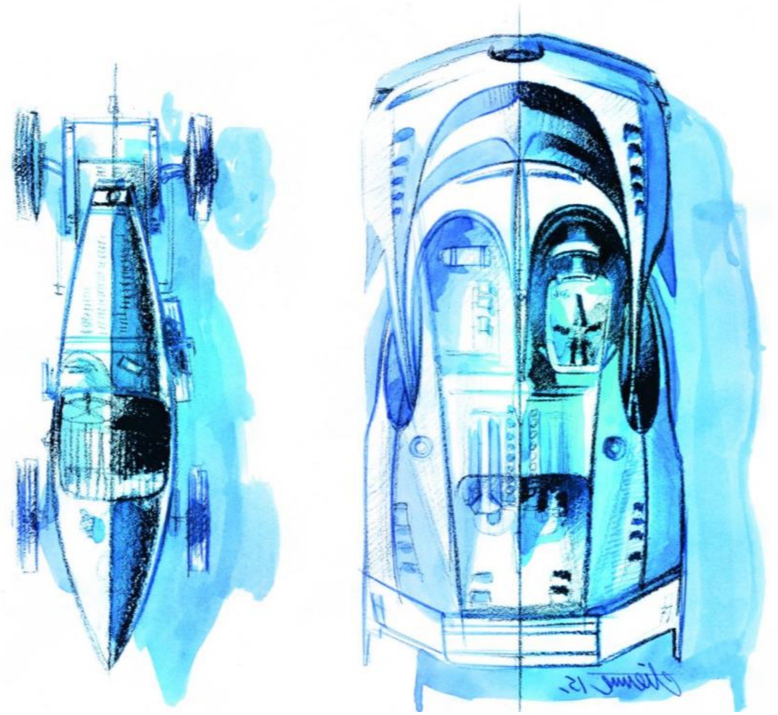
5. SUMMARY AND OUTLOOK

Summary:

- Development of an optimisation process considering lap time as objective function based on a meta-model with dependency modelling to reduce calculation time
- Meta-model has a precision between 99 to 99.95 % and is well suited for qualitative analysis
- Optimisation results for different tracks are fitting the respective track character

Outlook:

- Link an “offline” optimisation to identify the relevant areas for the vehicle parameters with an “online” optimisation for the subsequent detailed optimisation
- Investigate other tracks and synthesis of an abstracted track to reduce calculation time
- Expand the dependency model taking into account the thermal behaviour of the vehicle (drivetrain, tyres)



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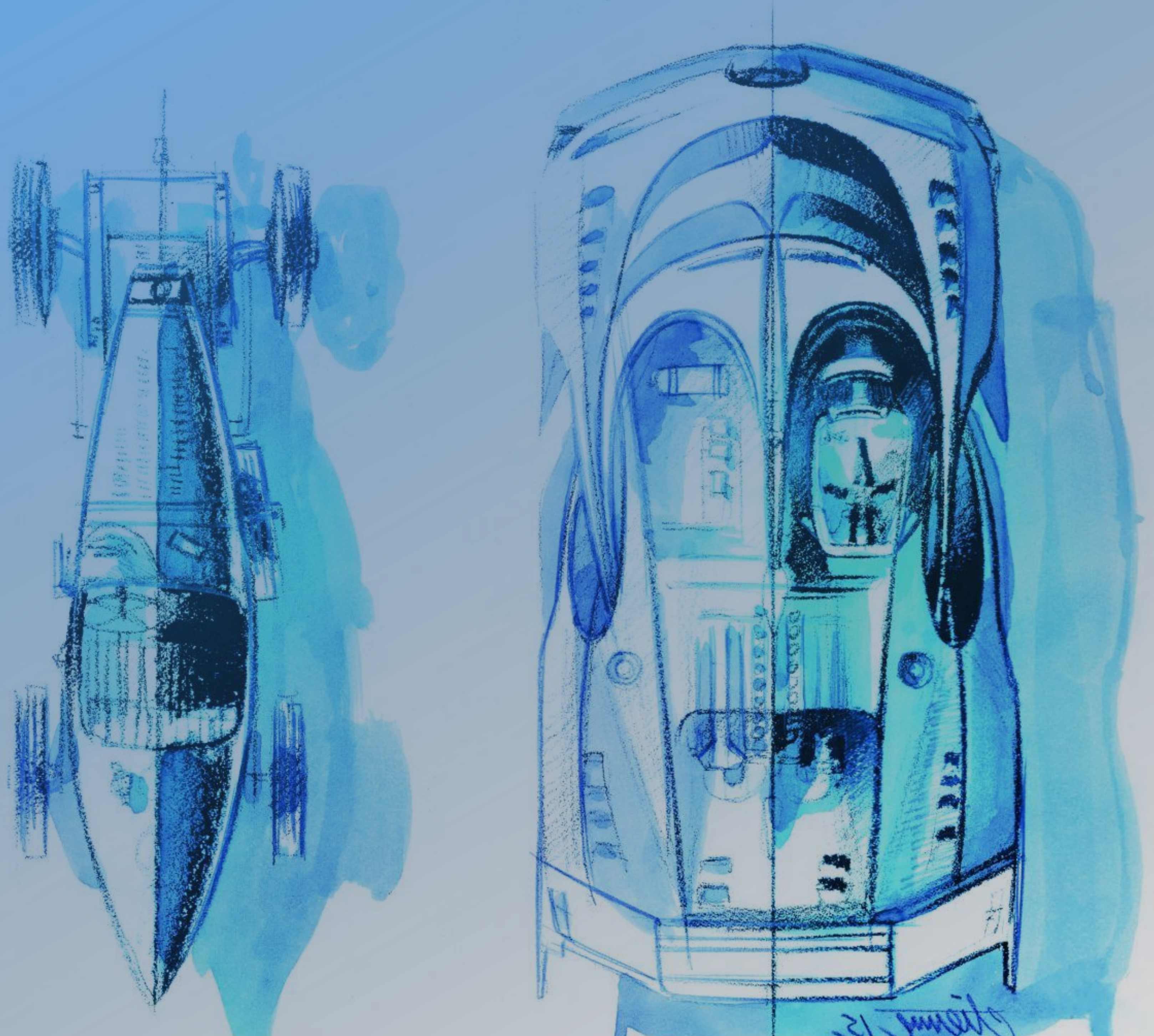
Thank You



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